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# Assessing State of the Art on Artificial Neural Network Paradigms for Level of Eutrophication Estimation of Water Bodies

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**ABSTRACT**

With growing power of computer and blend of intelligent soft wares, the interpretation and analytical capabilities of system had shown an excellent growth, providing intelligence solutions to almost every computing problem. In this direction here we are trying to identify how different geocomputation techniques had been implemented for estimation of parameters on water bodies so as to identify the level of contamination leading to different level of eutrophication. The main mission of this paper is to identify state-of-art in artificial neural network paradigms that are prevailing and effective in modeling and combining spatial data for anticipation. Among this our interest is to identify different analysis techniques and their parameters that are mainly used for quality inspection of lakes and estimation of nutrient pollutant content in it, and different neural network models that offered the forecasting of level of eutrophication in the water bodies. Different techniques are analyzed over the main steps;-assimilation of spatial data, statistical interpretation technique, observed parameters used for eutrophication estimation and accuracy of resultant data.

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## 1. INTRODUCTION

Eutrophication is a process of increase of nutrient content in water bodies, such as lakes, estuaries, rivers, or slow-moving streams that accelerates the plant growth such as algae, periphyton and plant weeds in excess. This enhanced growth of plants is known as an algal bloom, which in turn results with a low concentration of dissolved oxygen a state known as hypoxic and decaying of certain feeble plant species over others were favored, and is likely to cause severe reductions in water quality. The nutrients content would reach water bodies from many sources, such as fertilizers applied to agricultural fields, landfills near rivers; deposition of nitrogen from the atmosphere; erosion of soil; sewage treatment plant discharges etc. Eutrophication decreases the resource value of rivers, lakes, and estuaries having adverse affect on water usage for irrigation, fishing, aquatic life of plants and animals thus making water ecosystem unbalance. Sever health problems emerge where eutrophic conditions interfere with drinking water treatment. As per article published in by Jin [1] showed that all lakes studied were undergoing the eutrophication process. In the year 1970's, most of the lakes were with 91.8% water accounts, mesotrophic stage. In the next decade the percentage of lakes with oligotrophic status decreased by approximate 3%-0.5% and eutrophication increases by 5%-55%. By the year 2008 about 60% of lakes in china were in eutrophic and hypertrophic condition and further predicted that by 2030 all urban lakes would share the same status.

Eutrophication is one of the largely growing pollution problems in inland water bodies around the globe, thus restoration of water bodies need to have intelligent computation techniques in order to analyze over the current status of aquatic ecosystem along with alarming about the future characteristics by time series forecasting. With this fast computing world and emerging technology data analyzer need to be powered by artificial intelligent techniques. As the interpreter, modulator and predictor neural networks had emerged as a capable technique that generates approximate accurately complicated non-linear input-output relationships. A neural network is parallel-distributed processor that posses property inspired by human cognition system. ANN have the ability of computing, processing, prediction and classification of data and had advantages of nonlinearity, input-output mapping, adaptively, generalization and failure resistive [2].

In this direction, we are going to discuss some computing techniques used for interpretation and estimation of water bodies' status on eutrophication level taking in account spatial and temporal data as input parameters. This paper is further divided into Section II which briefs about geocomputation with major techniques as pattern recognition, spatial data analysis and artificial intelligence techniques. In the next part; Section III, related papers are surveyed and compares the identification of techniques used by the researchers in computing spatial data and generation of desired results. Section IV concludes with the model or architecture for the formulation of a system for enhanced inferences on eutrophication estimation.

## 2. TAXONOMY OF GEOCOMPUTATION

Geocomputation is an emerging field with a wide scope of research, that proponent the involvement of computation based approaches such as neural networks, heuristic search and computational automata design for spatial data analysis. This new interdisciplinary field beyond just implementation of statistical techniques for spatial data with basic essence of cognition in them thus coined as "geocomputation" by Openshaw and Abrahart, [3] and expanded by Longley and Brooks [4], that describes the use of computer-intensive methods for knowledge discovery in geography, especially those that employ non-conventional data clustering and analysis techniques and further elaborated to include spatial data analysis, dynamic modeling, visualization and space-time dynamics.

The major geocomputation evolution factors were: computerized data-rich environments and capability of computer to record and process over big data, affordable computational power; with emerge of virtualization and currently cloud computing implementations which provides high computation at lower costs, and lastly all the research efforts towards statistical techniques and mining algorithms and architecture that spatial data analysis and mining techniques took this ahead. For further enhancement in this area more computational research should be endorse with computer-based pattern search, exploratory spatial data analysis techniques, artificial intelligence approaches with more powerful heuristic searches algorithms, knowledge processing systems and dynamic modeling that could leverage real-time scenario of physical landscapes and other attributes.

We had investigated only the major techniques that encountered in the analysis of imagery geospatial data for computing characteristics of lake water conditions and these are as follows:

### 2.1. Spatial Data Analysis and Mining Techniques

Geographical Information Systems (GIS) are large domain computing systems that facilitate capturing, storage, retrieval, managing and analyses of spatial data that had geographical content in them. These systems utilize different geospatial analyzing techniques to impart accurate and meaningful results out of accessing structured imagery data received from the imagery satellites.

As defined by Bwozough, cited in [5], spatial analysis in GIS involves mainly three types of operations: 1) *Attribute Query* which is also known as *non-spatial* (or *spatial*) *query*, 2) *Spatial Query* and 3) *Generation of new data sets* from the original database. Combining all three steps the whole process starts with simple attribute query about spatial data and next comes the processing of spatial query and lastly, the new data set is generated from these queries that serve as an alternative data source or information. Every spatial data before analysis undergoes for *spatial autocorrelation*, which is a value additive step recognized as an essential feature in spatial data preprocessing stage, and following measures such as the *correlation coefficient, Moran index, join count statistic, Geary's C, Getis-Ord G statistic* and the *semi-variogram plot* have been employed to assess the global association of the data sets [6].

### 2.2. Geovisualization/Computer Based Pattern Recognition

Geovisualization is one of the most important aspects as it smoothes the progress of analysis by conversion of imagery data into the tabular form where different statistical analysis techniques could be implemented. Apart from two and three-dimensional mapping, that includes analyzing over the physical surface and connection among different terrains natural as well as man-made. MacEachren & Kraak [7]

characterized the major aspects of Geovisualization and assembled them in a process represented by a three-dimensional cube with *explore*, *analyze*, *synthesize* and *present* as major tasks.

The initial step of Geovisualization is about exploring and analyzing geographical data which is a spatial data captured from highly precise and powerful sensors of various satellites and stored into computational devices for further references. It starts with processing of satellite imagery data using digital image processing tools which then get converted into the tabular form that could easily interpret using different statistical techniques. The spatial data collected is further put into for auto-correction, interpolation, pruning, normalization and stored in a meaningful format. Synthesize is all about delivering the new outcomes out of raw data in more meaningful and after implementation of series of statistical techniques and methods. The last step of presentation is basically to represent the information into more a generalized format known as knowledge which also incorporates the visualization of geographical images on global maps like Google map or any other GIS tools which could result in predictions of different aspect and status of physical aspects of the earth.

While implementation of geostatistical techniques, some of these commonly used multivariate techniques are cluster analysis (CA), factor analysis/principal components (FA/PCA) and discriminant analysis (DA) which results into an effective data management network, monitoring system for spatial data reducing the on ground sampling cost, labor and effort that results more accurate picture of landscape variations.

The author in his work [8] demonstrated that water samples from major sampling stations were collected in due time span and exploratory analysis of data was made by box plots, ANOVA, display methods (principal component analysis) and unsupervised pattern recognition (cluster analysis) to analysis over the source of variations of water quality. Point source analysis for pollution identification, nutrient origination sources like municipal wastewater were demonstrated and thus classification of river water samples was achieved using PCA and cluster analysis.

In the studies presented by Alberto et al., [9] and Singh et al., [10], both spatial and temporal data for rivers are evaluated for quality analysis, where different parameters from scattered stations are collected formulating a complex data matrix, and then treated using the cluster analysis (CA) that renders good results as a first exploratory method to evaluate both spatial and temporal differences, factor analysis/principal components (FA/PCA) which were helps in identifying group components and discriminant analysis (DA) that showed best results for reduced data dimensions in large datasets. This study presents inevitability and usefulness of multivariate statistical techniques for evaluation and interpretation of the large number of complex data on water quality with a sight to access better information and further designing an effective monitoring and management network for water resources.

Geographical Information System (GIS) are meant for resource management and is an efficient decision-making tool however, powered with lots of sophisticated technology it is not ready used by common peoples because of lack of facility to distribute the analyzed information in an efficient manner. In further advancement, Caquard et al., [11], proposed the cartographic representation of water quality mapping information which can propagate the customized result on bases of variation in clientele. With the use of interpolation and extrapolation technique, visual data is put into for correlation and clustering analysis, along with the same gradation of colors are used to represent the level of water quality from lower to higher. The pattern recognition using some powerful learning techniques are additives that making the geographical view more realistic to the human eyes. Further to impart the higher resolution and moving ahead on adding dimensions to the perspective views, animation techniques had also enhanced the geovisualization experience.

### 2.3. Machine Learning Techniques

Artificial Intelligence explored a new horizon of intelligent machines that are enabled with cognition power with the huge database to store and process information so as to impart knowledge and facilitates in the day today working environment. Unlike statistical techniques which are expert in predicting sense out of linear data, machine learning techniques would stand for analyzing over non-linear data set which actually prevail real world representation. Câmara et al, [12] in the initial phase of emergence of geocomputation advocated towards the exploit of computational-intensive techniques such as neural networks, heuristic search and cellular automata for spatial data analysis.

With the evolution of techniques like Artificial Neural Networks (ANNs), Support Vector Machines (SVMs) and Cellular Automata (mainly for simulation of machines behavior), these approaches marked their importance in analyzing spatial and temporal data because of their native ability towards modeling of complex nonlinear datasets. ANNs are enabled with the ability for supervised as well as unsupervised learning modeling for basic tasks like classification, clustering, and prophecy that can be drawn out of regression analysis of empirical data sets.

Another machine learning method i.e. Kernel methods mentioned by Boser et al., [13], with kernel actions usages for mapping with higher dimensional features space without explicit computation of maps. Research in geospatial data modeling is molding towards intelligent software tools developed that are developed under the framework of Machine Learning Office, and few to mention are topo-climatic modeling, natural hazard assessments, which includes; heavy rainfall resulting in landslides, avalanches in higher altitudes, pollution mapping; air and soil pollution along with indoor radon and heavy metals presence, natural resources assessments, remote sensing imagery data classification, socio-economic data analysis and geovisualisation, etc. [14].

The Figure 1 shown below depicted a broad taxonomical breakdown with major technology that covers the whole aspect of geocomputation.

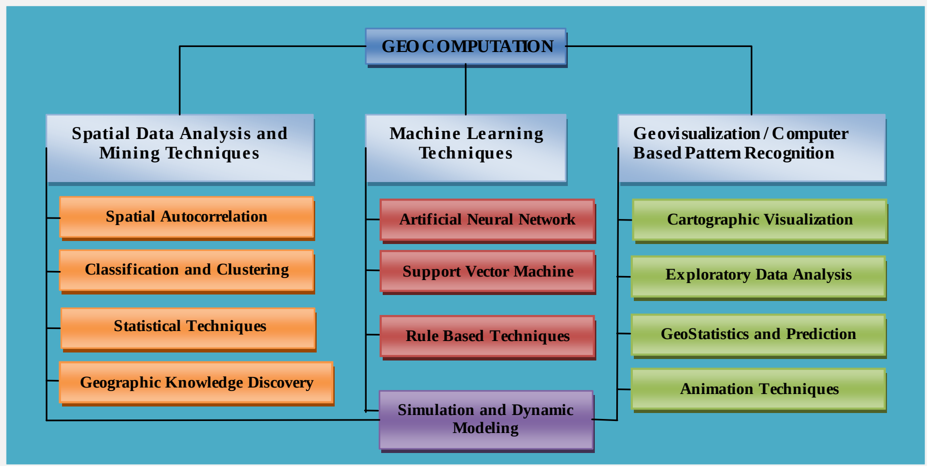


Figure 1. Taxonomy of Geocomputation Techniques

## 3. STATE OF THE ART

In this section the different techniques on eutrophication evaluation are discussed with the main focus on the tradition methods and their methodologies which still are the basic building block of every geocomputing system that deals with the similar type of problem appraisal. The two main sections explain the data essimilation from eutrophicated water body and management of these data for further decision making or in restoration mechanisms. The next subsection presents the state of the art in neural network for various similar water quality examination problems where the primary data are spatial data from different satellite sensors with variant metadata and of variant type of sources like lake, ocean, sea etc.

### 3.1. Data for Eutrophication Management and Control

Water is the main stream of life on earth and presently along with the scarcity of water, its quality is also a prominent issue to deal with thus we had preferred the problem of eutrophication of water bodies for which we are trying to identify the geocomputation techniques implemented to measure the current scenario on quality and futuristic methodologies. As mentioned in the publication (http://www.unep.or.jp) [31] , different ways of monitoring for the impacts of eutrophication and to establish management options are: 1) *chemical monitoring*: that focus on total phosphorus content measurement however, it is Nitrogen which had more significance over nutrient content valuation for eutrophication estimation , also chemical monitoring is more difficult in a lake or reservoir environment.; 2) *bio-assessment*: which accounts over main resultant of eutrophication i.e. abundant growth in biomass, which in turn measure for chlorophyll-a and also concentration of particulate organic carbon (POC) content, however not very apt for routine monitoring system.; and 3) *estimated techniques*: which includes *point source* and *non-point source estimation techniques* that found most apt for eutrophication monitoring system which includes phosphorous data together with other knowledge on land, demography etc., that could easily integrated for elucidation. However these may vary over results because of various factors like; spatial factors, auto-correction, classification and other techniques that are used for analysis and this is more about accuracy in computation techniques.

Geo spatial data from satellites are easily available among which Landsat imagery being widely used with data from three major sensors: Multi-spectral Scanner (MSS), TM (Thematic Mapper) and ETM+

(Enhancer Thematic Mapper Plus) where Baruha et al., [15], Sudheer et al., [16], Canziani et al., [17], and Guan et al., [18], make uses of these imagery spatial data for analysis of water quality using different geocomputation techniques. Also some data from SPOT satellite images, MODIS imagery and IRS P6 sensors imagery were exploited to study the sediment and nutrient level in water bodies, Mohamed et al., [19], Xue et al., [20], and Sheela et al, [21] respectively.

### 3.2. Artificial Neural Network Models

Limited water quality data and the high cost of water quality monitoring often pose serious problems for process-based modeling approaches to modulate the same for time series forecast. ANNs provide reasonable implementation options, because they are computationally very fast and require many fewer inputs parameter and inputs conditions than deterministic models. On the other hand to behave cognitively they do requisite for a large pool of representative data sets for training and appropriate learning algorithms.

ANNs are experimented for its usefulness in water quality prediction; nevertheless SVM had also demonstrated good results for same. A comparative study on ANN and SVM in [22], showed the superior result by later technique where authors predicted water quality of rivers by estimating total nitrogen and total phosphorus observed. In another research by Liao et al., [23], water quality is assessed using SVM and genetic algorithm which proved to deliver acceptable results and also efficient enough for classification of water quality. Chu et al., [24] proposed a case study where Hopfield neural network is embedded with Factor Analysis (FA) techniques to form Factor Analysis-Hopfield Neural Network (FAHNN) to identify the assessment factors for water quality measurement that proved to provide more reliable judgment and valuable information as compared with alike techniques.

The result imparted by the models also depends on number of data set and used training approach along with the learning techniques and tools which together have a direct impact on the quality of results announced by the system. ANNs are able to approximate accurately complicated non-linear input-output relationships. Firstly ANNs is requiring training or calibration on the basis of lots of statistical data. After training, ANN is being tested or verified for some input whose output is already known. The ANN techniques are flexible enough to accommodate additional constraints that may come up in the application. Moreover, ANN model can reveal hidden relationships in the chronological data, thus aiding the estimation of nutrient pollutant. There are more applications of prediction based implications of neural network like forest covered area, land usage modeling, natural resource estimation, natural calamity (flood, landslide, cyclone etc.) effected area analysis and much more which had a direct impact on natural resource management and planning systems.

Among the initial application of neural network modeling in evaluation of imagery data from satellite sensors (using LandsatTM) by Baruha et al. [15] and Panda et al. [25], the research comes out with some promising results which effective and simple implementation on the estimation of lake water quality mainly concentration of chlorophyll and solid sediments. Unlike the former which uses the most common model Back Propagation neural network model, later implemented Radial basis function neural (RBFN) network. They were found to be better over traditional regression analysis and were quite useful in the manifesting basic characteristic model of variant sized water bodies. Analyzing over optical distinctiveness of selective bands from LandSat5 TM and LandSat7 ETM+ imagery data, a methodology was presented by Canziani et al. [17], to infer the tropical state index of lakes. ANN model with multilayer perceptron and back propagation training algorithm were implemented to determine chlorophyll-a and total suspended solids concentrations which prove to be apt in understanding the complex dynamic behavior of water bodies.

The latest work presented in by Mohamed et al. [19], was inspired by researchers Moses et al. [26] and Gholamalifard et al. [27] using Multilayered Perceptron (MLP) neural network model on satellite images IRS P6 LISS III and Landsat respectively, that contributes towards detection of Lake Bathymetry using artificial neural network modeling on reflectance of green, red, both and four band combinations of SPOT image, as compared with polynomial correlation algorithm with reflectance from green band and Generalized Linear Model (GLM) with reflectance from green and red band. It demonstrates that ANNs impart more accurate results in terms of least value of root mean square than other conventional methods for bathymetric application, also the ANN using all bands having precedence to the other with single band usage.

In order to reach to the perspective outlook the power of artificial neural network was assessed for water quality estimation on inland water bodies, as to recognize the status of algal bloom in water body is also an essential part which further facilitates the restoration of process. With the same focus, Xue et al. [20] applied the algal bloom index to *in situ* remote sensing reflectance and MODIS Rayleigh-corrected reflectance along with the speed of local wind. The simple statistical technique, Classification and Regression (CART) Model is applied to the above data in order to identify the vertical profile distribution of phytoplankton biomass. The study concludes that similar decision tree approach could be used with other

satellite imagery data for monitoring and continues assessment of the level of eutrophication to other hydro bodies.

IRS P6 LISS III imagery data from is being analyzed to predict Secchi disk depth (SDD) of a lake with the usage of Multilinear Regression (MLR) model using all four bands (green, red, NIR and MIR) as independent variable and SDD dependent variable [21]. The computed results are found to be superior to regression model on spectral ration and individual band analysis and water found to be at hypereutrophic level.

In the work of Chen et al. in [28], three neural network models Radial Basis Function Neural Network (RBFN), Adaptive Network based Fuzzy Inference System (ANFIS) and Multilinear Regression (MLR) were developed and compared to examine over mean absolute error, the root mean square error and the correlation coefficient. These models were developed mainly to predict over dissolved oxygen, total phosphorus, chlorophyll-a and Secchi disk depth in the reservoir among which neural network ANFIS showed to be most suitable for simulating the water quality parameters with reasonable accuracy. A short outcome of the assessment is depicted in the tabulation format mentioned as the Table 1.

Table 1. Artificial Neural Network in Assessment of over Different Parameters of water bodies

| Citations | Input Parameters (Imagery/ Statistical Data Source) | ANN Model and Training Approach | Major Functionality | Key facets |
|---|---|---|---|---|
| Baruha et al., 2001[15] | LandsatTM Imagery | Back Propagation Neural Network with single hidden layer | To estimate chlorophyll concentration and sediments of water bodies | LandsatTM preferred over MODIS and SeaWiFs sensor cause of low spatial resolution |
| Panda et al., 2004 [25] | Landsat TM Imagery | Linear Regression statistical model (LMR) Radial basis function neural (RBFN) network | To determining the concentrations of chlorophyll-a (chl-a) and suspended matter (SM) | Cost-effective, quick, and feasible with accuracy in predicted and actual results. Information for all bands preferred over single band. RBNF to be more robust than LMR |
| Canziani et al., 2008 [17] | LandSat 5TM and LandSat 7 ETM+ Imagery | Multilayer Perceptron with Back Propagation Learning algorithm | To determine chlorophyll-a and total suspended solids concentrations for understanding the complex dynamic behavior of water bodies. | Remote sensors data processed by ANN are useful for monitoring the transformations in shallow lakes |
| Gholamalifard et al., 2013 [27] | Landsat 5TM | Multilayer Perceptron used with Back Propagation Learning algorithm | To extract the bathymetry information of southeastern Caspian Sea | ANN estimated depth with good accuracy even with relatively less *in situ* data sets and fairly poor sensor imagery. |
| Moses et al., 2013 [26] | IRS P6 LISS III imagery | Three-layered feed forward neural network with back propagation training algorithm | To estimate Lake bathymetry also estimating Secchi Disk Transparency (SDT) | All four band data set used and system imparts improved prediction accuracy |
| Xue et al., 2015 [20] | MODIS Imagery | Classification and Regression Tree Model (CART) Statistical Techniques | To identify vertical distribution profile of phytoplankton based on algal bloom index of Lake Chaohu. | Same approach with other satellite data could be applicable for monitoring of algal biomass in other similar hydrology. |

## 4. FUTURE SCOPE AND CONCLUSIONS

From our study we had identified that usage of imagery data; mainly Landsat TM, for secchi disk depth (SDD) and tropical state index (TSI) are known to be estimated for inland lakes in our region by researchers, [29] and [30]. Now for our future research direction we are intended to develop a overall geocomputing system which would analyze imagery data, extract the SDD, TSI, chlorophyll-a, dissolved oxygen and other parameters, train the neural network with following so as to learn the basic characteristics of selected water body and predict the current and future status of eutrophication using time series prediction so as to facilitate the restoration phenomenon.

In this assessment, we reviewed over the type of imagery data exercises by different systems and artificial neural network model and there learning techniques. The main objective was to explore the power of various neural network model in geocomputation and to draw a road map for some more technologically advanced systems that would be cognizant and if deployed could be easy to predict the futuristic behavior of water bodies ultimately envisage the quality of water in the system.

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